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Multiplicative structural decomposition and attribution analysis of carbon emission intensity in China, 2002–2012

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ABSTRACT

Energy/emission intensity indicators measure the relationship between economic development and climate change. These intensity indicators are preferentially used in assessment criteria for mitigation goals in places such as China. This paper investigates the driving factors of changes in the national CO_2 emission intensity and their contributions to reductions at the sector level in China from 2002 to 2012 using multiplicative structural decomposition analysis (SDA) and attribution analysis. Both Leontief and Ghosh input-output models are used in the study. The empirical results indicate: 1) the energy intensity effect is the main driver that decreases the aggregate emission intensity from both the demand and supply sides; 2) structural effects, such as the energy structure effect and domestic Ghosh structure effect, promote the increase in aggregate emission intensity principally; and 3) to a large extent, sector "smelting and pressing of metals", "manufacture of non-metallic mineral products" and "chemical industry" are the top three sectors that contribute to the negative energy intensity effect. Ultimately, several discussions and conclusions associated with the empirical results, result stability and research extensibility are presented.

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1. Introduction

The excessive carbon emissions brought on by energy consumption-driven economic growth have attracted great attention around the world. Most previous studies have shown that economic activity was the major driver for the increase in CO_2 emissions (Li et al., 2017; Su et al., 2017; Shen et al., 2018). In this regard, improvement of the intensity indicator, which is defined as the ratio of CO_2 emissions to economic activity, should be interpreted as a rebalance between environmental protection and economic development. In recent years, the emission intensity indicator, namely, the CO_2 emissions per unit of Gross Domestic Product (GDP), has been studied frequently, especially for the developing countries such as China (Xia et al., 2015; Su and Ang, 2015, 2016; Dong et al., 2018; Wang et al., 2018). In addition, the intensity indicator is preferred when a government plans to establish a mitigation goal, such as the intended nationally determined contributions of China, India, Mexico and Singapore (Su and Ang, 2015; Wang et al., 2017a). Thus far, the intensity indicator has been popularly acknowledged and utilized within academic and practical fields.

To achieve the rebalance, China endeavors to adjust the economic development pattern and has made its commitments using the intensity indicator. China has promised to reduce its CO_2 emission intensity by 40–45% by 2020 on the basis of the 2005 level. In addition, China further promised to reduce carbon emission intensity by 60–65% by 2030 on the basis of the 2005 level (NDRC, 2015). Naturally, the influencing factors of CO_2 emission intensity are numerous, such as the emission coefficient, energy utilization, production structure, and so on. From the practical perspective, it is of significance to identify the key factors in terms of the influences and their degree of impact in order to achieve the 2020/2030 goals. From the academic perspective, it is fundamental to choose and build the appropriate methods to describe and study the above issue.

Index decomposition analysis (IDA) and structural decomposition analysis (SDA) are two popular and widely used methods that are used to quantitatively study the influencing factors of an

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aggregate indicator. Within environmental research, IDA is based on energy/emissions at the sector level, whereas SDA is focused on the economy-wide changes in energy/emissions based on the input-output (I-O) technique (Su and Ang, 2012a, 2012b). Taking advantage of time series data, IDA can detect direct influences, such as the overall activity level, energy/emission intensity, energy structure and emission coefficients (Chen and Yang, 2015; Liobikienė et al., 2016; Cruz and Dias, 2016). Nevertheless, with the help of input-output tables, SDA can identify both direct and indirect drivers, such as the Leontief structure effect, inputs substitution and final demand structure (Duarte et al., 2013; Li and Wei, 2015; Kim et al., 2015). Detailed comparisons between IDA and SDA can be found in Hoekstra and van den Bergh (2003) and Su and Ang (2012a). In this study, SDA under an input-output model framework is preferred, aiming at CO_2 emission intensity at the national level.

There are two decomposition forms within SDA, namely, additive and multiplicative decompositions. Additive decomposition is expressed as the sum of the decomposed effects, which is usually implemented to the absolute indicator, such as energy consumption and CO_2 emissions (Cellura et al., 2012; Su and Ang, 2012a). Multiplicative decomposition is expressed as the product of the decomposed effects, which is usually implemented with intensity and elasticity indicators, such as energy consumption intensity (Fan and Xia, 2012; Zhang and Lahr, 2014a) and CO_2 emission intensity (Xia et al., 2015; Su and Ang, 2015). In terms of SDA research, the applications of additive decomposition are abundant (Liang et al., 2016; Wei et al., 2017; Wang and Yang, 2016). However, the multiplicative decomposition is seldom adopted due to the complexity associated with model development and the difficulty in interpreting results at the sector level (Su and Ang, 2012a, 2014a). In consideration of CO_2 emission intensity, this paper adopts multiplicative SDA and the related attribution analysis to investigate influencing factors and sectoral contributions.

The foundation of SDA is input-output (I-O) models, which can be divided into the Leontief model and the Ghosh model. Within environmental research, the Leontief I-O model is always adopted for consumption-based analysis (Su et al., 2010; Su and Ang, 2012a). On the other hand, the Ghosh I-O model is built from the supply perspective and is applied to income-based analysis (Su and Ang, 2015; Liang et al., 2016). In light of the differences between the Leontief and Ghosh I-O models (Yan et al., 2016), the analyses and results associated with CO_2 emission intensity are different. In consideration of research completeness, it has been suggested that the Leontief I-O model and Ghosh I-O model, which is regarded as a beneficial supplement, should be adopted simultaneously (Wu and Chen, 1990; Su and Ang, 2015). In SDA studies, researchers have adopted additive SDA based on the Leontief and Ghosh I-O models (Zhang, 2010; Liang et al., 2016) and have obtained rich and comprehensive results. It could be expected that multiplicative SDA based on the Leontief and Ghosh I-O models would also work well, but needs more attention (Su and Ang, 2015; Wang et al., 2017b). Within the economy-energy-environment system of China, multiplicative SDA based on the Leontief and Ghosh I-O models could allow us to identify the influencing factors of CO_2 emission intensity from both the demand and supply perspectives simultaneously.

This paper is the first and the most detailed research using multiplicative SDA and attribution analysis based on different I-O models to study CO_2 emission intensity in China. The main contributions are: 1) Both the Leontief and Ghosh I-O models are used to carry out the analysis from both the demand and supply sides, respectively. Accordingly, we expect to obtain rich and comprehensive results which could show the necessity and superiority of simultaneously adopting the Leontief and Ghosh I-O models. 2) The combination of multiplicative SDA and attribution analysis allows us to obtain the decomposition results not only at the aggregate level but also at the sector level, consistently and in a multiplicative way. 3) To reduce the potential impacts caused by sector and temporal aggregation, all official published and latest Chinese I-O tables (including benchmark and extended I-O tables) are adopted during the research period. With the most detailed database, the chaining analysis is carried out under an SDA framework. It is worth noting that Chinese energy consumption grew at half of the rate of GDP growth during the 1980s and 1990s. This trend reversed immediately after 2001 (Zhang and Lahr, 2014a). In terms of rapid growth in energy consumption and the latest data availability, the research period of this paper is from 2002 to 2012.

The remaining sections are organized as follows. Section 2 explores the development of the method and the research gap through reviewing studies of SDA and attribution analysis, especially those done in a multiplicative way. Section 3 describes the detailed formulation of the model and empirical database. The empirical results for the multiplicative SDA of aggregate CO_2 emission intensity and the attribution analysis of energy intensity effects are summarized in Section 4. Section 5 discusses the results and future research. Section 6 concludes the study.

2. Literature review

There are three popular decomposition methods implemented in SDA, namely, the traditional *ad hoc*, D&L and Logarithmic Mean Divisia Index (LMDI) methods (Su and Ang, 2012a). The traditional *ad hoc* decomposition method has always been applied to decomposition analysis when the number of driving forces is relatively large or within the two-stage decomposition (Chang et al., 2008; Lim et al., 2009; Kim et al., 2015). D&L and its approximate method are commonly applied in the field of energy/CO_2 emissions, embodied at national (Liang et al., 2016), regional (Wei et al., 2017) and industrial (Lin and Xie, 2016) levels. LMDI, proposed by Ang and Choi (1997), was the first ideal decomposition in IDA and exact decomposition in SDA. LMDI was first applied in SDA by Wachsmann et al. (2009) and the related guide for implementation is provided in Ang (2015). In recent years, LMDI has been gradually applied in the SDA model for direct and indirect energy/CO_2 emissions at both the national and regional levels (Dong et al., 2010; Wang et al., 2015; Deng et al., 2016; Wang and Yang, 2016). Additionally, more detailed SDA studies from before 2010 have been reviewed and summarized by Su and Ang (2012a).

Within the environmental field, the additive SDA scheme is the unique choice with regard to application studies before 2010. At that time, another decomposition scheme, or multiplicative SDA, was only applied in economic research, such as labor productivity growth (Dietzenbacher et al., 2000), labor costs (De Boer, 2009) and consumption per worker (Dietzenbacher et al., 2007) but was not involved in the energy and emissions fields (Su and Ang, 2012a; Wang et al., 2017b). Fortunately, multiplicative SDA based on the Leontief I-O model has been gradually applied in the economic-environmental system in recent years. Fan and Xia (2012) studied changes in China's energy intensity and investigated five driving forces behind its changes from 1987 to 2007. Zhang and Lahr (2014a) decomposed the change in national energy consumption and energy intensity into five driving forces and performed a detailed analysis from the view of China's economic structure, technology, urbanization and lifestyle. Zhang and Lahr (2014b) described the regional disparities of energy consumption in China. In their study, the effects of production structure and final demand were further decomposed into 3 and 2 sub-effects, respectively. From the global perspective, Zhong (2015) launched

an SDA based on a world input-output model to study the energy consumption, aggregate energy intensity, total CO_2 emission and total CO_2 intensity of 40 economies. The results indicated that the intensity effect is the most significant retardant in reducing energy and carbon intensity. At the regional level, Su and Ang (2016) proposed a spatial SDA framework to study the variations in aggregate emission intensity between countries or between regions in a country. Both additive and multiplicative decomposition models were applied to 30 regions of China. Recently, Su and Ang (2017) proposed the aggregate embodied intensity (AEI) indicator at the aggregate, final demand and sector levels from the demand perspective and investigated the driving forces of AEI at different levels in China (2007–2012).

Attribution analysis is proposed under the background of IDA (Choi and Ang, 2012), which is used to allocate aggregate effects to the sub-category. Attribution analysis has been widely used based on multiplicative LMDI (Choi and Oh, 2014; González, 2015; Andrés and Padilla, 2015) in IDA. Recently, attribution analysis has been further combined with IDA and production-theoretical decomposition analysis (PDA) to study the changes in sector level carbon intensity (Wang et al., 2018). Under the SDA framework, there are also some studies related to attribution analysis based on additive SDA that extract the individual effects directly from the decomposition formula (Wood, 2009; Wood and Lenzen, 2009; Wachsmann et al., 2009). However, the studies regarding attribution analysis based on multiplicative SDA are scarce due to the difficult allocation of aggregate effects (Su and Ang, 2014a). In multiplicative SDA, the commonly used decomposition method is the multiplicative D&L, which is the same as the generalized Fisher index in IDA (Dietzenbacher et al., 2000; Ang et al., 2004). On this basis, Su and Ang (2014a) extended the attribution analysis of the generalized Fisher index in SDA so that the multiplicative decomposition effect can be provided at the detailed sector level.

In consideration of CO_2 emission intensity, multiplicative SDA is more applicable and convenient due to easy interpretation (Su and Ang, 2015). The methodological issues in multiplicative SDA are discussed in detail by Wang et al. (2017c). So far, most multiplicative SDA studies have been based on the Leontief I-O model. However, studies that have adopted multiplicative SDA that are simultaneously based on the Leontief and Ghosh I-O models are scarce, as is further attribution analysis at the sector level. In this paper, the establishment and application of multiplicative SDA and attribution analysis are an endeavor to develop the SDA method within an input-output model framework, especially for the Ghosh I-O model.

3. Methods and data

According to responsible allocation principles, there are two types of CO_2 emission intensities involved in this paper. Specifically, consumption- and income-based CO_2 emission intensities are estimated under the frameworks of the Leontief and Ghosh I-O models, respectively. Furthermore, temporal SDA and attribution analysis are built in a multiplicative way. A non-competitive imports assumption was adopted, which focuses on domestic production and demand and differentiates between domestic and imported intermediate inputs (Su and Ang, 2013).

3.1. Consumption-based CO_2 emission intensity

The standard Leontief I-O model can be expressed under a non-competitive imports assumption as (Leontief, 1970; Su and Ang, 2013):

$$X = Z_d \cdot 1 + (y_d + y_e) \tag{1}$$

$$A_d = Z_d \cdot \left(\widehat{X}\right)^{-1} \tag{2}$$

$$X = (I - A_d)^{-1}(y_d + y_e) = L_d \cdot y_{tot} \tag{3}$$

where X is the (n*1) vector of total outputs; Z_d is the (n*n) matrix of domestic intermediate demands; y_d is the (n*1) vector of domestic final demand; y_e is the (n*1) vector of exports; A_d is the (n*n) matrix of domestic production coefficients; L_d is the (n*n) domestic Leontief inverse matrix; y_{tot} is the (n*1) total final demand vector (including domestic household consumption, domestic government consumption, domestic gross capital formation and exports); and I is a (n*n) identity matrix.

The economy wide total CO_2 emissions from the demand side can be represented as:

$$\begin{aligned} C^L &= f_v v \\ &= f_v\left(\widehat{k} \cdot X\right) = f_v \widehat{k} \cdot L_d \cdot y_{tot} = f_v H_d \cdot y_{tot} \end{aligned} \tag{4}$$

where C^L is the total consumption-based CO_2 emission; f_v is the (1*n) vector of total CO_2 emission per unit of value added; v is the (n*1) vector of value added; k is the (n*1) vector of primary input coefficient; and H_d is the (n*n) matrix of total domestic value added requirements coefficients.

Under the Leontief I-O framework, GDP can be calculated using the production approach as:

$$GDP^L = 1' v = 1'\left(\widehat{k} \cdot X\right) = 1'\left(\widehat{k} \cdot L_d \cdot y_{tot}\right) = 1' \cdot H_d \cdot y_{tot} \tag{5}$$

According to Eqs. (4) and (5), the consumption-based CO_2 emission intensity can be formulated as:

$$r^L = C^L \Big/ GDP^L = \frac{f_v H_d \cdot y_{tot}}{1' \cdot H_d \cdot y_{tot}} \tag{6}$$

3.2. Income-based CO_2 emission intensity

The standard Ghosh I-O model under a non-competitive imports assumption (Ghosh, 1958; Su and Ang, 2013) can be formulated as:

$$X' = 1' \cdot Z_d + 1' \cdot Z_i + v' \tag{7}$$

$$B_d = \left(\widehat{X}\right)^{-1} \cdot Z_d \tag{8}$$

$$X' = \left(m' + v'\right)(I - B_d)^{-1} = \left(m' + v'\right) G_d \tag{9}$$

where X is the (n*1) vector of total inputs; Z_d is the (n*n) matrix of domestic intermediate inputs; Z_i is the (n*n) matrix of imports for intermediate inputs; B_d is the (n*n) matrix of domestic allocation coefficients; $m = Z_i' \cdot 1$ is the (n*1) vector of imports for intermediate inputs at the sector level; G_d is the (n*n) domestic Ghosh inverse matrix; and I is a (n*n) identity matrix.

The economy wide total CO_2 emission from the supply side can be represented as:

$$C^G = f_x X = f_x G_d'(m + v) \tag{10}$$

where C^G is the total income-based CO_2 emission; and f_x is the (1*n)

vector of total CO_2 emission per unit of total outputs.

Under the Ghosh I-O framework, GDP can be calculated using the production approach as:

$$GDP^G = 1'v \tag{11}$$

According to Eqs. (10) and (11), the income-based CO_2 emission intensity can be formulated as:

$$r^G = C^G \Big/ GDP^G = \frac{f_x G_d'(m+v)}{1'v} \tag{12}$$

3.3. Multiplicative SDA of aggregate CO_2 emission intensity

To investigate several important drivers of aggregate CO_2 emission intensity, we rewrite Eq. (6) and (12) as follows:

$$r^L = \frac{\left(\widehat{E_e S_e'}\right) \cdot I_v' H_d \cdot S_y}{1' \cdot H_d \cdot S_y} \tag{13}$$

$$r^G = \left(\widehat{E_e S_e'}\right) \cdot I_o' G_d' (S_{mv} + S_v) \tag{14}$$

where E_e is the (1*m) vector of the CO_2 emission coefficient of energy consumption; S_e is the (n*m) matrix of the energy consumption structure; I_v is the (n*1) vector of energy consumption per unit of value added at the sector level; $S_y = y_{tot} \big/ (1' y_{tot})$ is the (n*1) vector of the total final demand structure; I_o is the (n*1) vector of energy consumption per unit of total output at the sector level; $S_{mv} = \frac{m}{1'v}$ is the (n*1) vector of imports for intermediate inputs per unit of value added; $S_v = \frac{v}{1'v}$ is the (n*1) vector of the value added structure; m refers to the number of energy sources; and n refers to the number of the sectors involved in the economy system.

According to the multiplicative decomposition framework (Su and Ang, 2015), the change in the consumption-based CO_2 emission intensity in Eq. (13) can be decomposed as:

$$D_{tot}^L = \frac{r_L^1}{r_L^0} = D_{E_e}^L \cdot D_{S_e}^L \cdot D_{I_v} \cdot D_{H_d} \cdot D_{S_y} \tag{15}$$

where D_{tot}^L refers to the total change in consumption-based CO_2 emission intensity from time 0 to 1; $r^1{}_L$ and $r^0{}_L$ refer to the consumption-based CO_2 emission intensity at times 1 and 0, respectively; $D_{E_e}^L$ refers to the Leontief emission coefficient effect; $D_{S_e}^L$ refers to the Leontief energy structure effect; D_{I_v} refers to the value added related energy intensity effect; D_{H_d} is the domestic Leontief structure effect; and D_{S_y} is the domestic final demand structure effect.

In terms of the fractional form in Eq. (13), the multiplicative decomposition must be done to the numerator and denominator simultaneously. Then, D_{tot}^L can be represented as:

$$D_{tot}^L = \frac{D_{tot}^{Ln}}{D_{tot}^{Ld}} = \frac{D_{E_e}^{Ln} \cdot D_{S_e}^{Ln} \cdot D_{I_v}^n \cdot D_{H_d}^n \cdot D_{S_y}^n}{D_{H_d}^d \cdot D_{S_y}^d} \tag{16}$$

where n and d denote different effects within the decompositions at the numerator and denominator, respectively. In detail, the effects in Eq. (15) can be derived through the following equations as:

$$\begin{aligned} D_{E_e}^L &= D_{E_e}^{Ln} \\ D_{S_e}^L &= D_{S_e}^{Ln} \\ D_{I_v} &= D_{I_v}^n \\ D_{H_d} &= D_{H_d}^n \Big/ D_{H_d}^d \\ D_{S_y} &= D_{S_y}^n \Big/ D_{S_y}^d \end{aligned} \tag{17}$$

Similar to Eq. (15), the change in the income-based CO_2 emission intensity in Eq. (14) can be decomposed as:

$$D_{tot}^G = \frac{r_G^1}{r_G^0} = D_{E_e}^G \cdot D_{S_e}^G \cdot D_{I_o} \cdot D_{G_d} \cdot D_{S_{mv}} \cdot D_{S_v} \tag{18}$$

where D_{tot}^G refers to the total change in income-based CO_2 emission intensity from time 0 to 1; $D_{E_e}^G$ refers to the Ghosh emission coefficient effect; $D_{S_e}^G$ refers to the Ghosh energy structure effect; D_{I_o} refers to the output related energy intensity effect; D_{G_d} refers to the domestic Ghosh structure effect; $D_{S_{mv}}$ refers to the m-v ratio effect; and D_{S_v} refers to the value added structure effect.

Decomposition analysis was revealed as an arbitrary problem leading to the instability of results. As a result, D&L in SDA and S/S in the IDA method were proposed to solve the above issue by considering all n! equivalent exact decomposition forms. However, the number of equivalent exact decomposition forms increases exponentially as the number of factors increases. In other words, there will be 120 and 720 equivalent exact forms in Eq. (15) and Eq. (18), respectively, in this paper. Supporting this, the disadvantage of the D&L (also the S/S) method comes from computational complexity. Dietzenbacher and Los (1998) proposed an approximate D&L method (i.e., average of two polar decompositions) to achieve balance between result accuracy and computational complexity. In addition, the result accuracy that is derived based on the approximate technique is satisfied in the decomposition analysis (Su and Ang, 2012a) and attribution analysis (Su and Ang, 2014a), respectively. At the practical level, the complete D&L method is often adopted when the number of the factors is relatively small (Liu et al., 2010; Cellura et al., 2012; Duarte et al., 2013). Otherwise, the approximate method may be considered (Fan and Xia, 2012; Xia et al., 2015; Lin and Xie, 2016). Additionally, the D&L method can address zero and negative values in the input-output table. Therefore, the average polar decomposition form (Dietzenbacher and Los, 1998) is adopted in this paper.

In this section, only the value added related energy intensity effect in Eq. (15) and output related energy intensity effect in Eq. (18) are described in Eqs. (19-20). Other individual effects are presented in Appendix A in detail.

$$D_{I_v} = \sqrt{\left(\frac{V_{00111}}{V_{00011}}\right) \cdot \left(\frac{V_{11100}}{V_{11000}}\right)} \tag{19}$$

$$D_{I_o} = \sqrt{\left(\frac{U_{001111}}{U_{000111}}\right) \cdot \left(\frac{U_{111000}}{U_{110000}}\right)} \tag{20}$$

where $V_{ttttt} = \left(\widehat{E_e^t S_e^t}\right) \cdot I_v^t H_d^t \cdot S_y^t \ (t = 0, 1)$, $U_{tttttt} = \left(\widehat{E_e^t S_e^t}\right) \cdot I_o^t G_d^t \left(S_{mv}^t + S_v^t\right) \ (t = 0, 1)$.

3.4. Attribution analysis of the energy intensity effect

Attribution analysis is used to quantify individual contributions to the aggregate change with respect to a certain effect. In concept, the multiplicative D&L method in SDA is similar to the generalized Fisher index method in IDA. The framework of attribution analysis based on the generalized Fisher index proposed by Su and Ang (2014a) is adopted for the Leontief I-O model based energy intensity effect. In addition, we extend the attribution analysis to the Ghosh I-O model framework to study the output related energy intensity effect.

Under the Leontief I-O model framework, the value added related energy intensity effect (D_{I_v}) can be rewritten according to Eq. (19) as:

$$D_{I_v} = \left(\frac{V_{00111}}{V_{00011}}\right)^{\frac{1}{2}} \cdot \left(\frac{V_{11100}}{V_{11000}}\right)^{\frac{1}{2}} \tag{21}$$

The transformation and expansion equation of the first term on the right-hand side of Eq. (21) can be written as:

$$\begin{aligned}&\sum_{i=1}^{n}\left(\frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^1 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00111}} - \frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^0 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00011}}\right)\\ &= \sum_{i=1}^{n} L\left(\frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^1 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00111}}, \frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^0 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00011}}\right)\\ &\quad \times \left[\ln\left(\frac{I_{vi}^1}{I_{vi}^0}\right) - \ln\left(\frac{V_{00111}}{V_{00011}}\right)\right] = 0\end{aligned} \tag{22}$$

where $L(a,b) = (a-b)/(\ln a - \ln b)$ is the logarithmic mean function and i denotes the energy intensity, energy consumption structure and domestic Leontief structure of sector i.

Solving Eq. (22), we obtain the following equations:

$$\ln\left(\frac{V_{00111}}{V_{00011}}\right) = \sum_{i=1}^{n} w_{i,1}^{I_v} \ln\left(\frac{I_{vi}^1}{I_{vi}^0}\right) \tag{23}$$

$$w_{i,1}^{I_v} = \frac{L\left(\frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^1 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00111}}, \frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^0 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00011}}\right)}{\sum_{i=1}^{n} L\left(\frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^1 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00111}}, \frac{E_e^0 S_{ei}'^0 \cdot I_{vi}^0 \cdot \left(H_{di}^1 S_y^1\right)}{V_{00011}}\right)}, \quad \sum_{i=1}^{n} w_{i,1}^{I_v} = 1 \tag{24}$$

Similarly, the solution that originates from the second term on the right-hand side of Eq. (21) is expressed as follows:

$$\ln\left(\frac{V_{11100}}{V_{11000}}\right) = \sum_{i=1}^{n} w_{i,2}^{I_v} \ln\left(\frac{I_{vi}^1}{I_{vi}^0}\right) \tag{25}$$

$$w_{i,2}^{I_v} = \frac{L\left(\frac{E_e^1 S_{ei}'^1 \cdot I_{vi}^1 \cdot \left(H_{di}^0 S_y^0\right)}{V_{11100}}, \frac{E_e^1 S_{ei}'^1 \cdot I_{vi}^0 \cdot \left(H_{di}^0 S_y^0\right)}{V_{11000}}\right)}{\sum_{i=1}^{n} L\left(\frac{E_e^1 S_{ei}'^1 \cdot I_{vi}^1 \cdot \left(H_{di}^0 S_y^0\right)}{V_{11100}}, \frac{E_e^1 S_{ei}'^1 \cdot I_{vi}^0 \cdot \left(H_{di}^0 S_y^0\right)}{V_{11000}}\right)}, \quad \sum_{i=1}^{n} w_{i,2}^{I_v} = 1 \tag{26}$$

Based on Eqs. (23)–(26), D_{I_v} can be expressed as a geometric mean index after logarithmic transformation as:

$$\begin{aligned}\ln D_{I_v} &= \frac{1}{2}\ln\left(\frac{V_{00111}}{V_{00011}}\right) + \frac{1}{2}\ln\left(\frac{V_{11100}}{V_{11000}}\right)\\ &= \sum_{i=1}^{n}\left(\frac{1}{2}w_{i,1}^{I_v} + \frac{1}{2}w_{i,2}^{I_v}\right)\ln\left(\frac{I_{vi}^1}{I_{vi}^0}\right) = \sum_{i=1}^{n} w_i^{I_v}\ln\left(\frac{I_{vi}^1}{I_{vi}^0}\right)\end{aligned} \tag{27}$$

$$w_i^{I_v} = \frac{1}{2}\left(w_{i,1}^{I_v} + w_{i,2}^{I_v}\right) \quad (i = 1, 2, \cdots, n) \tag{28}$$

where $w_{i,1}^{I_v}$, $w_{i,2}^{I_v}$, and $w_i^{I_v}$ represent weight coefficients across sectors and. $\sum_{i=1}^{n} w_i^{I_v} = 1$.

Then, Eq. (27) can be equivalently transformed into a multiplicative form as:

$$D_{I_v} = \prod_{i=1}^{n} D_{I_v,i} = \prod_{i=1}^{n}\left(\frac{I_{vi}^1}{I_{vi}^0}\right)^{w_i^{I_v}} \tag{29}$$

Practically, $w_i^{I_v}$ is the contribution degree from the change in the ith sector's value added related energy intensity to D_{I_v}. In addition, $D_{I_v,i}$ is the total contribution from the change in the ith sector's value added related energy intensity to D_{I_v}. It is worth noting that the geometric index expressions of D_{I_v} obtained through this method fulfill zero-value robustness.

Under the Ghosh I-O model framework, in the same vein, the output related energy intensity effect (D_{I_o}) can be transformed into a geometric mean index according to Eq. (20):

$$\begin{aligned}\ln D_{I_o} &= \frac{1}{2}\left(\frac{U_{001111}}{U_{000111}}\right) + \frac{1}{2}\left(\frac{U_{111000}}{U_{110000}}\right)\\ &= \sum_{j=1}^{n}\left(\frac{1}{2}u_{j,1}^{I_o} + \frac{1}{2}u_{j,2}^{I_o}\right)\ln\left(\frac{I_{oj}^1}{I_{oj}^0}\right) = \sum_{j=1}^{n} u_j^{I_o}\ln\left(\frac{I_{oj}^1}{I_{oj}^0}\right)\end{aligned} \tag{30}$$

$$u_{j,1}^{I_o} = \frac{L\left(\frac{E_e^0 S_{ej}'^0 \cdot I_{oj}^1 G_{dj}'^1\left(S_{mv}^1 + S_v^1\right)}{U_{001111}}, \frac{E_e^0 S_{ej}'^0 \cdot I_{oj}^0 G_{dj}'^1\left(S_{mv}^1 + S_v^1\right)}{U_{000111}}\right)}{\sum_{j=1}^{n} L\left(\frac{E_e^0 S_{ej}'^0 \cdot I_{oj}^1 G_{dj}'^1\left(S_{mv}^1 + S_v^1\right)}{U_{001111}}, \frac{E_e^0 S_{ej}'^0 \cdot I_{oj}^0 G_{dj}'^1\left(S_{mv}^1 + S_v^1\right)}{U_{000111}}\right)}, \quad \sum_{j=1}^{n} u_{j,1}^{I_o} = 1 \tag{31}$$

$$u_{j,2}^{I_o} = \frac{L\left(\frac{E_e^1 S_{ej}'^1 \cdot I_{oj}^1 G_{dj}'^0\left(S_{mv}^0 + S_v^0\right)}{U_{111000}}, \frac{E_e^1 S_{ej}'^1 \cdot I_{oj}^0 G_{dj}'^0\left(S_{mv}^0 + S_v^0\right)}{U_{110000}}\right)}{\sum_{j=1}^{n} L\left(\frac{E_e^1 S_{ej}'^1 \cdot I_{oj}^1 G_{dj}'^0\left(S_{mv}^0 + S_v^0\right)}{U_{111000}}, \frac{E_e^1 S_{ej}'^1 \cdot I_{oj}^0 G_{dj}'^0\left(S_{mv}^0 + S_v^0\right)}{U_{110000}}\right)}, \quad \sum_{j=1}^{n} u_{j,2}^{I_o} = 1 \tag{32}$$

$$u_j^{I_o} = \frac{1}{2}\left(u_{j,1}^{I_o} + u_{j,2}^{I_o}\right) \quad (j = 1, 2, \cdots, n) \tag{33}$$

where j denotes the energy consumption structure, energy intensity and domestic Ghosh structure of sector j; $u_{j,1}^{I_o}$, $u_{j,2}^{I_o}$ and $u_j^{I_o}$ are the weight coefficients across sectors; and. $\sum_{j=1}^{n} u_j^{I_o} = 1$.

Then, Eq. (30) can be equivalently transformed into a multiplicative form as:

$$D_{I_o} = \prod_{j=1}^{n} D_{I_o,j} = \prod_{j=1}^{n}\left(\frac{I_{oj}^1}{I_{oj}^0}\right)^{u_j^{I_o}} \tag{34}$$

Practically, $u_j^{I_o}$ is the contribution degree from the change in the

jth sector's output related energy intensity to D_{I_o}. In addition, $D_{I_o j}$ is the total contribution from the change in the jth sector's output related energy intensity to D_{I_o}.

3.5. Data

3.5.1. Input-output tables

In this paper, 2002, 2007 and 2012 Chinese benchmark I-O tables and 2005 and 2010 Chinese extended I-O tables (NBSC, 2006–2015) are used for analysis. Considering overestimation from the competitive import assumption, the original Chinese I-O tables in different years are compiled into the non-competitive imports (Su and Ang, 2013) style as shown in Table B.1. In this paper, the economy system is composed of 38 sectors, a number that is suggested for empirical study in China to promote stability of results (Su et al., 2010). Using both the benchmark and extended I-O tables can also help to reduce the impacts of temporal aggregation on the decomposition results, especially at the sector level (Su and Ang, 2012b). In detail, the explicit account setting is shown in Table B.2.

The original I-O table is compiled based on the price index of the current year. For multi-year research, we must unify the price index among different years. As a result, we adopt the 2002 price index to deflate the 2005, 2007, 2010 and 2012 I-O tables in this paper. Referenced by Yang and Lahr (2010), the primary industry applies an agricultural producer price index (NBSC, 2014); secondary sectors apply an industry producer price index (NBSC, 2013); and the tertiary and construction industries apply an implicit GDP price index (NBSC, 2014).

3.5.2. Energy and emissions data

In this paper, 17 kinds of energy consumption are involved for estimating CO_2 emissions including raw coal, cleaned coal, other washed coal, coke, coke oven gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, LPG, refinery gas, other petroleum products, natural gas and electricity. The energy consumption data for 38 sectors are allocated according to the "Data Treatment Scheme 2" (Su et al., 2010) and are from the China Energy Statistic Yearbook (NBSC, 2006–2013). In this paper, we remove the energy consumption for raw materials during the calculation of CO_2 emissions. Since we include electricity consumption, we do not consider the primary energy consumption of the electricity power sector to avoid double accounting. The detailed emission coefficients of the abovementioned energy (except electricity) are listed in Table C.3.

In addition, the emission coefficient of electricity is calculated according to Eq. (35) for different years. As shown in Fig. 1, the value of the electricity emission coefficients declined gradually during the research period.

$$\textit{electricity } CO_2 \textit{ emission coefficient} = \frac{\textit{direct } CO_2 \textit{ emission of primary energy from electric power sector}}{\textit{national electricity consumption}} \tag{35}$$

4. Empirical results

4.1. Multiplicative SDA of carbon intensity based on the Leontief I-O model

From the demand perspective, the consumption-based CO_2 emission intensity in Eq. (6) decreased continuously from 2.2414 t-$CO_2/10^4$ yuan in 2002 to 1.6223 t-$CO_2/10^4$ yuan in 2012, except for the year 2005. Accordingly, GDP in Eq. (5) increased from 12,163 billion yuan to 38,782 billion yuan. As shown in Fig. 2, the only increasing variation is between 2002 and 2005 by 0.0454 t-$CO_2/10^4$ yuan, or 4.3 percent. On the other hand, the largest decrease is between 2007 and 2010, a magnitude of 0.3395 t-$CO_2/10^4$ yuan, or 14.02 percent. The most rapid average annual reduction rate of emission intensity appears between 2005 and 2007 by 5.44%. As the carbon intensity reduction space shrinks, we intend to investigate the key factors to maintain the mitigation achievement and impetus.

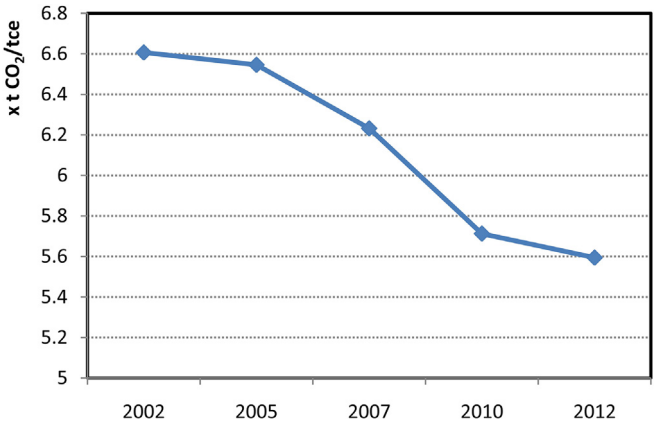

Fig. 1. CO_2 emission coefficients of electricity in China, 2002–2012.

Detailed decomposition results are shown in Fig. 3. The Leontief emission coefficient effect $D^L_{E_e}$ always contributed to a decrease in the CO_2 emission intensity, even to a small degree ($0.96<D^L_{E_e}<1$), which benefited from technological improvements in power generation. In contrast, the Leontief energy structure effect $D^L_{S_e}$ always contributed to a slight increase in the CO_2 emission intensity ($1<D^L_{S_e}<1.03$). In addition, the value added related energy intensity effect D_{I_v} was the major factor that led to the reduction of CO_2 emission intensity from 2005 to 2012 ($0.79<D_{I_v}<0.93$). The domestic Leontief structure effect D_{H_d}, which reflects the production structure of the economy, contributed to a decrease in emission intensity from 2002 to 2005 and 2007–2010 (e.g., $D_{H_d}<1$) as well as an increase in the emission intensity from 2005 to 2007 and 2010–2012 (e.g., $D_{H_d}>1$). Such unstable performance is defined as

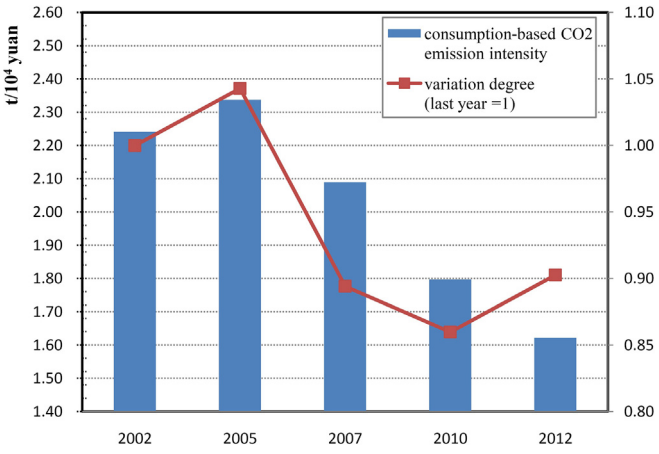

Fig. 2. Consumption-based CO_2 emission intensity in China, 2002–2012.

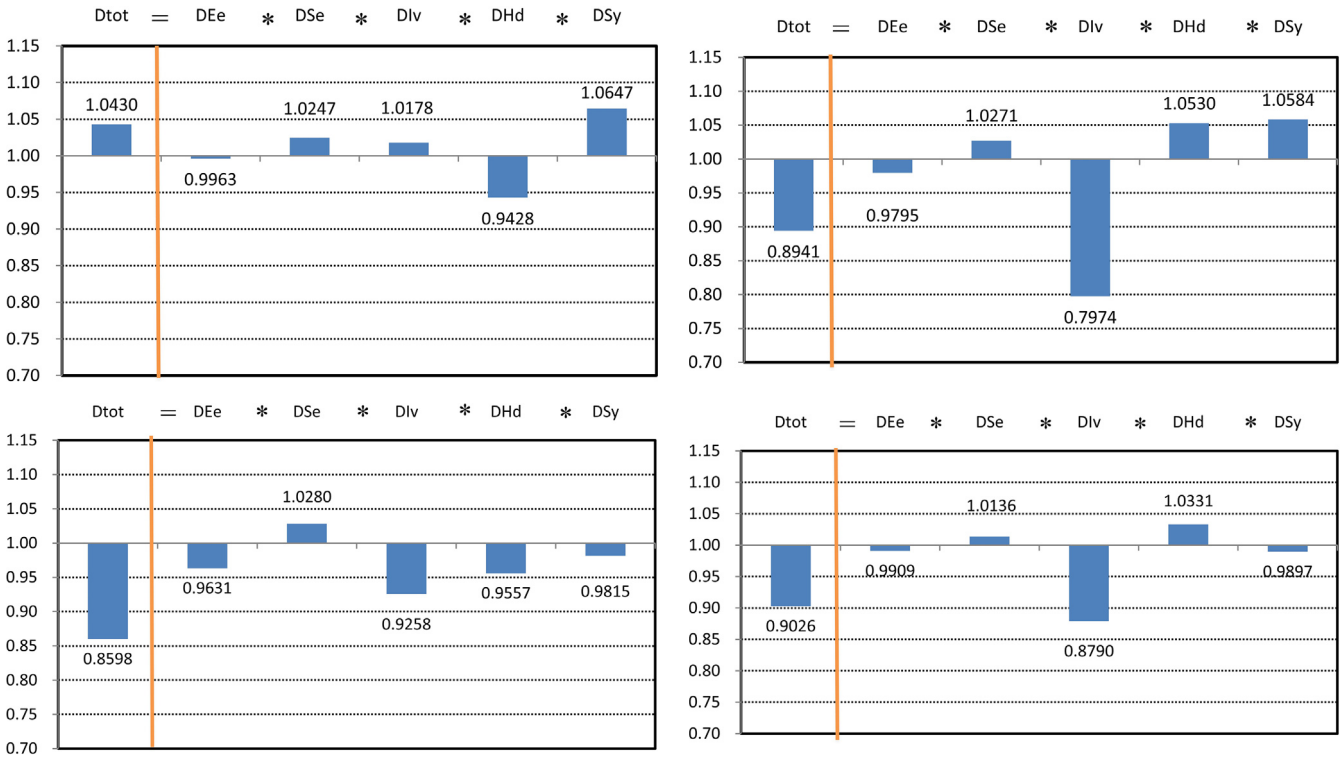

Fig. 3. Multiplicative SDA results of CO_2 emission intensity in China based on the Leontief I-O model, 2002–2012.

an antitone phenomenon, which is discussed in Section 5. Finally, the domestic final demand structure effect D_{S_y} was prone to the trend in the reduction of emission intensity, which increasingly turned from a positive effect in 2002–2007 into a negative effect in 2007–2012.

In contrast to the energy intensity effect, the structural effects such as $D^L_{S_e}$, D_{H_d} and D_{S_y}, are the main contributors to the increase in CO_2 emission intensity in China. Except for the unstable performance of the domestic Leontief structure effect, the Leontief energy structure effect and domestic final demand structure effect appear to improve as a result of decreasing positive effects. Within policy domain, structural reforms have already been proposed and have gained more attention from the Chinese government. In terms of the results in this section, it could be considered that the achievements caused by structural reforms may show a second large potential for carbon mitigation in China in the future. At present, the trend of CO_2 emission intensity is primarily determined by the energy intensity effect, which is further discussed in Section 4.3.

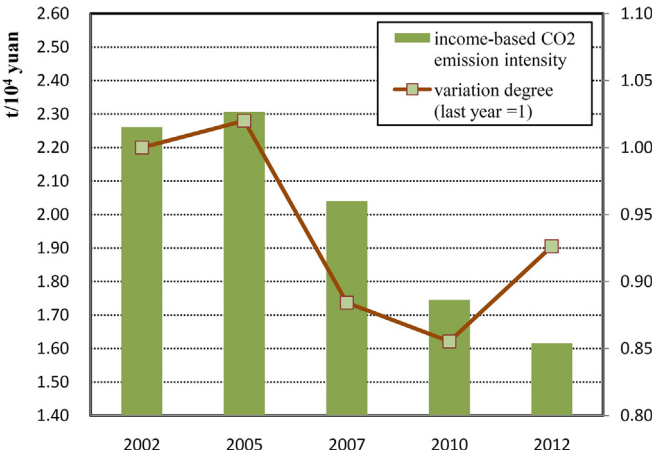

Fig. 4. Income-based CO_2 emission intensity in China, 2002–2012.

4.2. Multiplicative SDA of carbon intensity based on the Ghosh I-O model

From the supply perspective, the income-based CO_2 emission intensity in Eq. (12) decreased continuously from 2.2614 t-CO_2/10^4 yuan in 2002 to 1.6157 t-CO_2/10^4 yuan in 2012, except in 2005. Accordingly, GDP in Eq. (11) increased from 12,186 billion yuan to 38,920 billion yuan. As shown in Fig. 4, the only increasing variation is between 2002 and 2005 with a magnitude of 0.0454 t-CO_2/10^4 yuan, or 2.01 percent. On the other hand, the greatest decreasing variation is between 2007 and 2010 with a magnitude of 0.2951 t-CO_2/10^4 yuan, or 14.47 percent. The fastest average annual reduction rate of emission intensity appears between 2005 and 2007, by 5.97%. In general, the main conclusions of the macro-emission analysis derived from the Ghosh and Leontief I-O models are similar without considering numerical differences.

The detailed decomposition results are shown in Fig. 5. The Ghosh emission coefficient effect $D^G_{E_e}$ and the Ghosh energy structure effect $D^G_{S_e}$ always contributed to a decrease ($0.96<D^G_{E_e}<1$) and an increase ($1<D^G_{S_e}<1.03$) in the CO_2 emission intensity, respectively, to a small degree. It is worth highlighting that the output related energy intensity effect D_{I_o} was the major factor for the emission intensity reduction and always contributed to a considerable decrease from 2002 to 2012 ($0.84<D_{I_o}<0.94$). The domestic Ghosh structure effect D_{G_d}, which reflects the allocation structure of the supply, offset the negative effect from D_{I_o} leading to an increase in emission intensity between 2002 and 2010. Until 2012, D_{G_d} had a

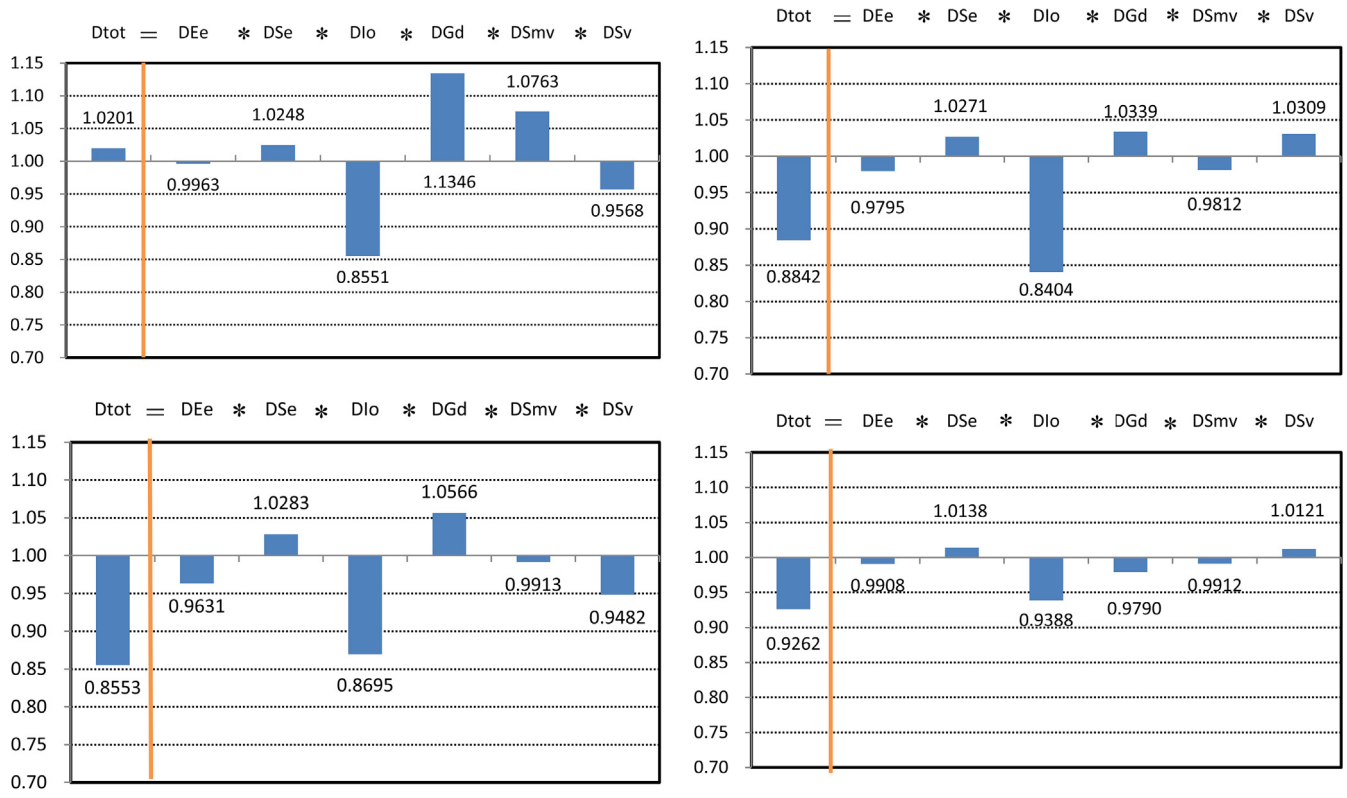

Fig. 5. Multiplicative SDA results of CO_2 emission intensity in China based on the Ghosh I-O model, 2002–2012.

negative effect at a relatively low level. The *m-v* ratio effect $D_{S_{mv}}$ had a positive effect in 2002–2005, which then turned into a negative effect in 2005–2012. Similar to D_{H_d} in Section 4.1, the results of the value added structure effect D_{S_v} also showed the antitone phenomenon. In other words, D_{S_v} was estimated to be less than 1 in 2002–2005 and 2007–2010 and greater than 1 in 2005–2007 and 2010–2012.

Since the Leontief and Ghosh I-O models are adopted simultaneously, more abundant results and comparisons are available, especially for structural effects. Similarly, the energy structure effect has always increased the carbon intensity slightly from both the demand and supply perspectives. Different from the unstable performance of the production structure, the allocation structure shows continuous improvement and a negative effect finally appears in 2012. Ultimately, the value added structure effect from the supply side, unlike the final demand structure effect from the demand side, performs unsteadily, which indicates a dissatisfactory signal for carbon intensity mitigation. In this regard, the production structure from the demand side and the value added structure from the supply side should be adjusted and optimized continuously through various measures of structural reforms.

4.3. Attribution analysis of energy intensity effect

Supported by the results, the energy intensity effect is the most crucial factor. It is necessary to attribute the aggregate effect to confirm the key industries. In this section, the detailed attribution results are presented from the demand and supply sides, respectively.

4.3.1. Attribution results of value added related energy intensity effect

In terms of Eq. (29), the detailed attribution results associated with the value added related energy intensity effect are presented in Fig. 6. From 2002 to 2005, the positive effect of aggregate energy intensity was determined by the "smelting and pressing of metals" sector (s12), which offset the remarkable negative effect from the "manufacture of non-metallic mineral products" sector (s11) ($D^{2002-2005}_{I_v,11,12} = 1.0103$). Among the 38 sectors, there were 14 sectors that contributed to the positive effect. In addition, the minority sectors had a significant positive effect, especially the "mining and washing of coal and extraction of petroleum and natural gas" (s2) and "agriculture, forestry, animal husbandry, fishery and related service industry" (s1) sectors. During the remainder of the research period, the negative effect of aggregate energy intensity mostly benefited from s12, and the individual effect values were 0.9006, 0.9335 and 0.9112 respectively in 2005–2007, 2007–2010 and 2010–2012. Among the 38 sectors, most of the sectors had negative effects, amounting to 29, 21 and 25 sectors during the time frames studied, respectively. In contrast, the s2, "processing of petroleum, coking and processing of nuclear fuel" (s9) and "transport and storage industry" (s23) sectors appeared to have a continuously

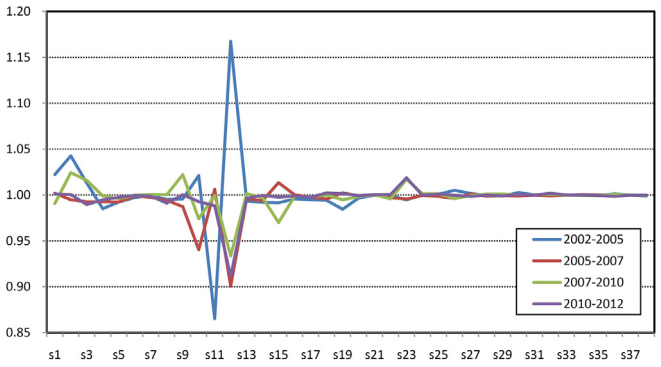

Fig. 6. Attribution of energy intensity per value added in China, 2002–2012.

positive effect, most notably from 2007 to 2012 ($D_{I_v,2,9,23}^{2007-2010} = 1.0653, D_{I_v,2,9,23}^{2010-2012} = 1.0194$).

Table 1 lists the important sectors with remarkable attribution results from the demand side. $w_i^{I_v}$ is the weight coefficient at the sector level, which has a range between 0 and 1, as mentioned in Section 3.4. According to the exponential function theory, under the condition of $D_{I_v,i} > 1$, the smaller value of $w_i^{I_v}$ tends to decrease the positive effect of the aggregate energy intensity much more. In contrast, when $D_{I_v,i} > 1$, the larger value of $w_i^{I_v}$ tends to increase the negative effect of the aggregate energy intensity much more. From 2002 to 2012, the largest values of $w_i^{I_v}$ were all within s12, so the value of $D_{I_v,12}$ determines the positive or negative effect of the aggregate energy intensity. In other words, the sector with a large weight coefficient will play a significant role in changing the CO_2 emission intensity of China. As a result, the top three sectors in terms of large weight coefficients are s12, s11 and s10. On the other hand, technological improvements in s23, s2 and s9, which are in favor of generating a negative energy intensity effect, will further facilitate mitigation in China.

4.3.2. Attribution results of output related energy intensity

In terms of Eq. (34), the attribution results associated with output related energy intensity based on the Ghosh I-O model are described in Fig. 7. It is worth noting that the definitions of energy intensity based on the Leontief and Ghosh I-O models are different. In this section, the negative effect of aggregate energy intensity was mainly driven by s11, s19 and s4 from 2002 to 2005 ($D_{I_o,11,19,4}^{2002-2005} = 0.8358$); by s12, s10 and s19 from 2005 to 2007 ($D_{I_o,12,10,19}^{2005-2007} = 0.8640$); by s12, s10 and s11 from 2007 to 2010 ($D_{I_o,12,10,11}^{2007-2010} = 0.9196$); and by s12 from 2010 to 2012 ($D_{I_o,12}^{2010-2012} = 0.9532$). On the other hand, the remarkable positive effects on energy intensity at the sector level, specifically within s12 and s1 from 2002 to 2005 and within s11 from 2005 to 2007, should be paid more attention. On the whole, the number of sectors that contributes to decreases in aggregate CO_2 emission intensity is always larger than that of the opposite situation, such as 30 sectors *vs* 8 sectors from 2010 to 2012.

Key sectors with large weight coefficients and remarkable individual contributions are listed in Table 2. As previously mentioned, when $D_{I_o,j} > 1$, a larger value of $u_j^{I_o}$ contributes to increasing the positive effect of the aggregate energy intensity, and vice versa. It is worth stressing that the weight coefficient cannot change the direction of positive/negative effects at the sector level, it can only amplify/shrink the magnitude of the effect. According to Table 2, s12, s11 and s10 are the top three crucial sectors that contribute to the negative effect of aggregate energy intensity. However, macro-adjustment of s23 and s19 should be given more attention in the near future, considering their mitigation potential.

In general, the fluctuation of the energy intensity effect across the sectors mainly comes from agriculture and the secondary industry. The tertiary industry performs steadily, as shown in Figs. 6 and 7. In addition, at the present stage, the performance of energy intensity in a few key industries determines the aggregate energy intensity effect, such as the performance in s12, s11 and s10. In fact, it is a good signal for this paper, but an uncertain factor for the carbon mitigation in the future. In other words, it is necessary to balance the mitigation weights among all of the sectors to gain the greater mitigation potential.

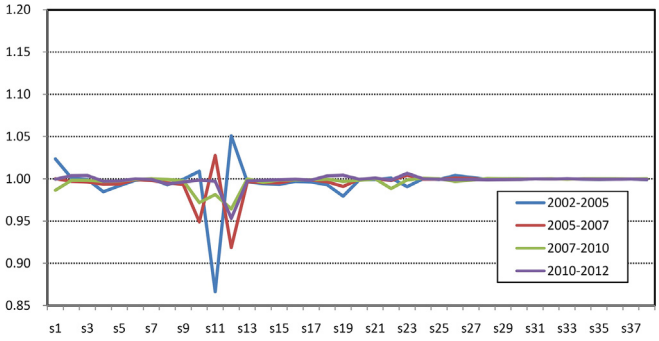

Fig. 7. Attribution of energy intensity per output in China, 2002–2012.

4.4. Uncertainty analysis

The instability of results may be caused by modeling and data processing. From the method perspective, the randomness of structural decomposition would lead to great differences in results. Referenced by Dietzenbacher and Los (1998), polar decomposition, namely, the approximate D&L method, is suggested to simultaneously achieve accurate results and simple computing. In addition, the selection of an imports assumption within the I-O model affects the results. Comparable to the competitive imports assumption, a non-competitive imports assumption distinguishes domestic production from imports. Accordingly, the non-competitive imports assumption is preferred, as it avoids the overestimation problem (Su and Ang, 2013).

From the data perspective, the temporal and sector aggregation issues have a major impact on the results. Since the time series I-O data are unavailable, it is necessary to balance the trade-offs between temporal and sector aggregation within SDA studies. As evidenced by the empirical study on China, utilizing a shorter time period of I-O data is more robust to temporal aggregation, especially over a long research period (Su and Ang, 2012b). As a result, Chinese benchmark and extended I-O tables are adopted simultaneously to achieve an approximate chaining analysis for a 10-year span. Obtained through the indirect complication method by NBSC, although the extended I-O tables may include some uncertainty, the data quality is relatively reliable (Zhang et al., 2015). With respect to sector aggregation, a more aggregated or more detailed data set may not be the desirable choice (Weber, 2009). According to Su et al. (2010) and Su and Ang (2012b), levels approximately 40

Table 1
Key sectors within the value added related energy intensity effect, 2002–2012.

Sector Code	2002–2005		2005–2007		2007–2010		2010–2012	
	$w_i^{I_v}$	$D_{I_v,i}$	$w_i^{I_v}$	$D_{I_v,i}$	$w_i^{I_v}$	$D_{I_v,i}$	$w_i^{I_v}$	$D_{I_v,i}$
s12	0.2403	1.1676	0.2931	0.9006	0.3004	0.9335	0.3010	0.9112
s11	0.1281	0.8653	0.1030	1.0062	0.1030	0.9994	0.1075	0.9884
s10	0.0993	1.0212	0.1006	0.9404	0.0952	0.9741	0.0945	0.9928
s23	0.0843	0.9948	0.0835	0.9955	0.0864	1.0173	0.0964	1.0187
s2	0.0579	1.0426	0.0482	0.9948	0.0488	1.0244	0.0470	1.0005
s9	0.0423	0.9958	0.0400	0.9874	0.0400	1.0222	0.0331	1.0002

Table 2
Key sectors within the output related energy intensity effect, 2002–2012.

Sector Code	2002–2005		2005–2007		2007–2010		2010–2012	
	$u_j^{I_o}$	$D_{I_o,j}$	$u_j^{I_o}$	$D_{I_o,j}$	$u_j^{I_o}$	$D_{I_o,j}$	$u_j^{I_o}$	$D_{I_o,j}$
s12	0.2411	1.0506	0.2856	0.9187	0.2988	0.9462	0.2994	0.9532
s11	0.1238	0.8665	0.1055	1.0275	0.1035	0.9814	0.1069	0.9971
s10	0.1043	1.0088	0.1027	0.9490	0.0969	0.9718	0.0951	0.9985
s23	0.0842	0.9907	0.0851	1.0042	0.0900	0.9987	0.0951	1.0064
s19	0.0419	0.9795	0.0405	0.9910	0.0403	0.9969	0.0398	1.0043
s4	0.0269	0.9847	0.0214	0.9935	0.0214	0.9970	0.0209	0.9970

sectors appear to be sufficient and satisfactory in the case of China. On the other hand, the energy and emissions related data may result in uncertainty due to some statistical, practical and other incentives that are inevitable and unquantifiable.

Based on the abovementioned factors, the processed data among different years are comparable and can reasonably describe the economic-energy-environment system of China in 2002–2012. As a consequence, the results presented in Section 4 are satisfactory.

5. Discussions

The emission coefficient effect, which benefits from technological improvements related to power generation, always appears to have a slightly negative effect. In contrast, the energy structure effect has a positive effect due to its high share in coal consumption. The utilization of renewable energy (such as photovoltaic generation and wind power generation) and the reform of energy prices (such as electricity and natural gas pricing mechanisms) will help to increase the consumption ratio of non-fossil energy.

The results of the domestic Leontief structure effect and value added structure effect highlight the antitone phenomenon, which may be introduced by the extended I-O tables. As mentioned in Section 4.5, the extended I-O table is estimated and compiled according to statistical materials, but not direct investigation. To identify the unstable structural effects, only the multiplicative SDA on basis of the benchmark I-O tables was performed. Supported by the new decomposition results, the domestic Leontief structure effect appears to be negative from 2002 to 2007 ($D_{H_d}^{2002-2007} = 0.9846$) and 2007–2012 ($D_{H_d}^{2007-2012} = 0.9939$). The value added structure effect shows a negative effect from 2002 to 2007 ($D_{S_v}^{2002-2007} = 0.9856$) and 2007–2012 ($D_{S_v}^{2007-2012} = 0.9581$). This indicates that both the production structure and value added structure facilitate carbon intensity reduction at the present stage. Additionally, the domestic production structure needs continuous adjustments as the inhibiting effect shrinks. In addition, the domestic Ghosh structure effect shows the positive effect ($D_{G_d}^{2002-2007} = 1.1504, D_{G_d}^{2007-2012} = 1.0357$). In this regard, the domestic Leontief structure effect performs inversely. Therefore, macroeconomic control should be more focused on the transformation of allocation structure. It is worth emphasizing that the allocation structure adjustments should be formulated under consideration of the close communication between production and the market.

With respect to the energy intensity effect, the “smelting and pressing of metals”, “manufacture of non-metallic mineral products” and “chemical industry” sectors are the top three sectors that contribute to the negative effect. In terms of the larger value of weight coefficients, the unit change in energy intensity in the above three industries will have greater influences on the aggregate energy intensity effect than those with lower values. In other words, the decline in the aggregate energy intensity effect mainly benefits from industries with both decreasing energy intensities and large weight coefficients. Accordingly, there are two ways to maintain and strengthen the downward trend of national energy/carbon intensity. On one hand, the energy intensities of the industries, which have large weight coefficients (such as the above three traditional industries), should be further decreased through technological improvements and reduced use of outdated capacity. On the other hand, the industrial structure should be adjusted toward increasing the weight coefficients of the industries, in which energy intensities are decreasing slightly and continuously (such as in the “manufacture of general and special purpose machinery”, “manufacture of transport equipments”, and “manufacture of computers, communication and other electronic equipment” sectors and other high-tech industries).

The multiplicative SDA and attribution analysis adopted in this paper is used to investigate the emission intensity issue based on a single region I-O model at the national level. With respect to application scope, the method aggregation could also be applied to water, waste, pollutants and other environmental intensity indicators, and recent proposed aggregate embodied intensities (Su and Ang, 2017). In terms of method development, the proposed method aggregation could easily be extended to the extended I-O models (Su et al., 2013; Liu et al., 2016), multi-region I-O models (Su and Ang, 2011, 2014b), and spatial SDA framework (Su and Ang, 2016). Due to the unavailability of consecutive year I-O tables of China, studies that adopt the SDA method based on chaining analysis are scarce. In terms of result stability, it is urgent to estimate the I-O tables of intervening years for China to implement chaining analysis to adopt SDA in future studies (Su and Thomson, 2016).

6. Conclusions

In this paper, we study the CO_2 emission intensity of China in 2002–2012 under the I-O framework. From the demand perspective, using 2005 as a benchmark year, the CO_2 emission intensity decreased by 5.09% annually through 2012. To achieve the 2020 and 2030 mitigation goals (introduced in Section 1), the CO_2 emission intensity needs to decrease annually by 3.35–3.91% and 3.6–4.11%, respectively, from 2005 to 2020. Based on the same benchmark year, from the supply perspective, the CO_2 emission intensity decreased annually by 4.66% through 2012. The corresponding boundaries of the annual decrease ratio for fulfilling the 2020 and 2030 mitigation goals are the same as those based on the Leontief I-O model. However, using 2012 as benchmark year, the CO_2 emission intensity is estimated to decrease annually by 1.8–2.86% and 2.18–2.7% from the demand perspective, or by 2.19–3.24% and 3.18–3.9% from the supply perspective by 2020 and 2030, respectively. Supported by the above results, it is expected to become more difficult to achieve the 2030 mitigation goal than the 2020 goal in China. In addition, it is much more difficult to fulfill the

reduction goal from the supply side than from the demand side. As a consequence, supply-side structural reform is urgent for China under the fundamental demand for sustainable development.

Suggested by the results, the secondary industry plays an important role in economic and environmental performance in China. According to the outline of the 13th Five Year Plan (2016–2020), the Chinese government emphasizes the innovation ability and basic capacity of manufacturing. As the main sources in early stages of mitigation, the traditional industries should be implemented industrial upgrades through allocation and energy structure adjustments. Meanwhile, the innovation and productivity of high-end manufacturing should be paid more attention. In other words, the high-tech industries that are environmentally friendly and provide high value-added products should be advocated for and improved in China. In conclusion, to achieve the 2030 mitigation goal, it is important to realize the mitigation subject transfer from traditional industries to high-tech industries.

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Appendix A. Multiplicative SDA formula of energy/emission intensities

According to the decomposition framework adopted in Section 3.3, the individual effects in Eq. (15) and (18) could be expressed following the average polar decomposition form.

For the Leontief I-O model, the expression of the consumption-based CO_2 emission intensity is in fractional form. As mentioned in Section 3.3, the numerator and denominator sections should be decomposed simultaneously. Specifically, the domestic Leontief structure effect (D_{H_d}) and the domestic final demand structure effect (D_{S_y}) are derived through two decomposition processes. The detailed expressions are derived as follows:

$$D_{E_e}^{L} = \sqrt{\left(\frac{V_{11111}}{V_{01111}}\right)\cdot\left(\frac{V_{10000}}{V_{00000}}\right)} \tag{A.1}$$

$$D_{S_e}^{L} = \sqrt{\left(\frac{V_{01111}}{V_{00111}}\right)\cdot\left(\frac{V_{11000}}{V_{10000}}\right)} \tag{A.2}$$

$$D_{I_v} = \sqrt{\left(\frac{V_{00111}}{V_{00011}}\right)\cdot\left(\frac{V_{11100}}{V_{11000}}\right)} \tag{A.3}$$

$$D_{H_d} = \frac{D_{H_d}^{n}}{D_{H_d}^{d}} = \frac{\sqrt{\left(\frac{V_{00011}}{V_{00001}}\right)\cdot\left(\frac{V_{11110}}{V_{11100}}\right)}}{\sqrt{\left(\frac{Z_{11}}{Z_{01}}\right)\cdot\left(\frac{Z_{10}}{Z_{00}}\right)}} \tag{A.4}$$

$$D_{S_y} = \frac{D_{S_y}^{n}}{D_{S_y}^{d}} = \frac{\sqrt{\left(\frac{V_{00001}}{V_{00000}}\right)\cdot\left(\frac{V_{11111}}{V_{11110}}\right)}}{\sqrt{\left(\frac{Z_{01}}{Z_{00}}\right)\cdot\left(\frac{Z_{11}}{Z_{10}}\right)}} \tag{A.5}$$

where $V_{ttttt} = \left(\widehat{E_e^t S_e^{'t}}\right)\cdot I_v^{'t} H_d^t \cdot S_y^t \quad (t = 0, 1)$, $Z_{tt} = 1^{'}\cdot H_d^t \cdot S_y^t \quad (t = 0, 1)$.

For the Ghosh I-O model, the expression of the consumption-based CO_2 emission intensity is in an integral form. As a result, the six effects in Eq. (18) can be derived as:

$$D_{E_e}^{G} = \sqrt{\left(\frac{U_{111111}}{U_{011111}}\right)\cdot\left(\frac{U_{100000}}{U_{000000}}\right)} \tag{A.6}$$

$$D_{S_e}^{G} = \sqrt{\left(\frac{U_{011111}}{U_{001111}}\right)\cdot\left(\frac{U_{110000}}{U_{100000}}\right)} \tag{A.7}$$

$$D_{I_o} = \sqrt{\left(\frac{U_{001111}}{U_{000111}}\right)\cdot\left(\frac{U_{111000}}{U_{110000}}\right)} \tag{A.8}$$

$$D_{G_d} = \sqrt{\left(\frac{U_{000111}}{U_{000011}}\right)\cdot\left(\frac{U_{111100}}{U_{111000}}\right)} \tag{A.9}$$

$$D_{S_{mv}} = \sqrt{\left(\frac{U_{000011}}{U_{000001}}\right)\cdot\left(\frac{U_{111110}}{U_{111100}}\right)} \tag{A.10}$$

$$D_{S_v} = \sqrt{\left(\frac{U_{000001}}{U_{000000}}\right)\cdot\left(\frac{U_{111111}}{U_{111110}}\right)} \tag{A.11}$$

where $U_{tttttt} = \left(\widehat{E_e^t S_e^{'t}}\right)\cdot I_o^{'t} G_d^{'t}\left(S_{mv}^t + S_v^t\right) \quad (t = 0, 1)$.

Appendix B. The format of the input-output table adopted for decomposition analysis

The format of the input-output table adopted in this paper is presented in Table B.1. In detail, the account setting is shown in Table B.2.

Table B.1
Structure of input-output table with a non-competitive import assumption.

		Domestic intermediate input				Total final demand		Total output
		s1	s2	… …	s38	Domestic final demand	Export	
Domestic intermediate input	s1	$Z^d{}_{11}$	$Z^d{}_{12}$	… …	… …	$y^d{}_1$	$y^e{}_1$	x_1
	s2	$Z^d{}_{21}$	$Z^d{}_{22}$		… …	$y^d{}_2$	$y^e{}_2$	x_2
	… …			$Z^d{}_{ss}$	… …	… …	… …	… …
	s38	… …	… …	… …	… …	$y^d{}_{38}$	$y^e{}_{38}$	x_{38}
Import		$Z^i{}_1$	$Z^i{}_2$	… …	$Z^i{}_{38}$	y_i		
Value added		v_1	v_2	… …	v_{38}			
Total input		x_1	x_2	… …	x_{38}			

Note: $Z^d{}_{ij}$ refers to the domestic intermediate input from sector i to j, $y^d{}_i$ refers to the domestic final demand of sector i, $y^e{}_i$ refers to exports of sector i, $Z^i{}_i$ refers to the imports for intermediate input of sector i, y_i refers to imports for final demand, v_i refers to the value added of sector i, and x_i refers to total input/output of sector i.

Table B.2
Account setting of input-output table of China.

Sector	Code	Sector	Code
Agriculture, forestry, animal husbandry, fishery and related service industry	s1	Production and supply of gas	s20
Mining and washing of coal and extraction of petroleum and natural gas	s2	Production and supply of water	s21
Mining and processing of ores	s3	Construction	s22
Manufacture of foods, beverages and tobacco	s4	Transport and storage industry	s23
Manufacture of textile	s5	Postal industry	s24
Manufacture of wearing, leather, fur, feather and related products	s6	Information transmission, computer services and software	s25
Processing of timber and manufacture of furniture	s7	Wholesale and retail trades	s26
Printing and manufacture of articles for culture, education, sport and entertainment activities	s8	Hotel and catering services	s27
Processing of petroleum, coking and processing of nuclear fuel	s9	Finance and insurance	s28
Chemical industry	s10	Real estate	s29
Manufacture of non-metallic mineral products	s11	Leasing and business services	s30
Smelting and pressing of metals	s12	Research and test development	s31
Manufacture of metal products	s13	Polytechnic services	s32
Manufacture of general and special purpose machinery	s14	Water conservancy, environment and public facilities management	s33
Manufacture of transport equipments	s15	Household service and other services	s34
Manufacture of electrical machinery and apparatus	s16	Education	s35
Manufacture of computers, communication and other electronic equipment	s17	Health, social security and social welfare	s36
Manufacture of measuring instruments and machinery and other manufacture (including utilization of waste resources)	s18	Culture, sports and entertainment	s37
Production and supply of electric power and heat power	s19	Public management and social organization	s38

Appendix C. Emission coefficients of different energy sources

Table C.3
CO_2 emission coefficients of fuel energy.

	Average low calorific value ($TJ/10^3$ t)	Unit calorific value (t C/TJ)	Carbon oxidation rate	Coal equivalent coefficient (tce/t)	CO_2 emission coefficient (t CO_2/tce)
raw coal	20.91	26.37	0.94	0.7134	2.6636
cleaned coal	16.34	25.8	0.92	0.8988	2.545
other washed coal	8.36	25.8	0.92	0.2853	2.545
coke	28.435	29.5	0.93	0.9703	2.948
coke oven gas	17.99[a]	12.1	0.99	0.6139[b]	1.2872
other gas	10.45[a]	12.1	0.99	0.3566[b]	1.2872
other coking products	33.46	29.2	0.93	1.1417	2.9118
crude oil	41.82	20.1	0.98	1.4269	2.1167
gasoline	43.07	18.9	0.98	1.4697	1.9903
kerosene	43.07	19.5	0.98	1.4697	2.0535
diesel oil	42.65	20.2	0.98	1.4554	2.1272
fuel oil	41.82	21.1	0.98	1.4269	2.222
LPG	50.18	17.2	0.99	1.7123	1.8279
refinery gas	46.06	15.7	0.99	1.5717	1.6685
other petroleum products	41.87	20	0.98	1.4287	2.104
natural gas	38.93[a]	15.3	0.99	1.3284[b]	1.6277

Note.
[a] The unit is MJ/m^3.
[b] The unit is kg ce/m^3.

References

Ang, B.W., 2015. LMDI decomposition approach: a guide for implementation. Energy Pol. 86, 233–238.
Ang, B.W., Choi, K.H., 1997. Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. Energy J. 18 (3), 59–73.
Ang, B.W., Liu, F.L., Chung, H.S., 2004. A generalized Fisher index approach to energy decomposition analysis. Energy Econ. 26 (5), 757–763.
Andrés, L., Padilla, E., 2015. Energy intensity in road freight transport of heavy goods vehicles in Spain. Energy Pol. 85, 309–321.
Choi, K., Ang, B.W., 2012. Attribution of changes in Divisia real energy intensity index-An extension to index decomposition analysis. Energy Econ. 34 (1), 171–176.
Choi, K., Oh, W., 2014. Extended Divisia index decomposition of changes in energy intensity: a case of Korean manufacturing industry. Energy Pol. 65, 275–283.
Cruz, L., Dias, J., 2016. Energy and CO_2 intensity changes in the EU-27: decomposition into explanatory effects. Sustainable Cities and Society 26, 486–495.
Chang, Y.F., Lewis, C., Lin, S.J., 2008. Comprehensive evaluation of industrial CO_2 emission (1989-2004) in Taiwan by input-output structural decomposition. Energy Pol. 36 (7), 2471–2480.
Cellura, M., Longo, S., Mistretta, M., 2012. Application of the structural decomposition analysis to assess the indirect energy consumption and air emission changes related to Italian households consumption. Renew. Sustain. Energy Rev. 16, 1135–1145.
Chen, L., Yang, Z., 2015. A spatio-temporal decomposition analysis of energy-related CO_2 emission growth in China. J. Clean. Prod. 103, 49–60.
De Boer, P., 2009. Multiplicative decomposition and index number theory: an empirical application of the Sato-Vartia decomposition. Econ. Syst. Res. 21 (2), 163–174.
Dong, Y., Ishikawa, M., Liu, X., Wang, C., 2010. An analysis of the driving forces of CO_2 emissions embodied in Japan-China trade. 38(11), 6784–6792.
Dietzenbacher, E., Los, B., 1998. Structural decomposition techniques: sense and sensitivity. Econ. Syst. Res. 10 (4), 307–323.
Dietzenbacher, E., Hoen, A.R., Los, B., 2000. Labor productivity in western Europe 1975-1985: an intercountry, interindustry analysis. J. Reg. Sci. 40 (3), 425–452.
Dietzenbacher, E., De Groot, O.J., Los, B., 2007. Consumption growth accounting. Rev. Income Wealth 53 (3), 422–439.
Deng, M., Li, W., Hu, Y., 2016. Decomposing industrial energy-related CO_2 emissions

in Yunnan province: switching to low-carbon economic growth. Energies 9 (1), 23.
Duarte, R., Mainar, A., Sánchez-Chóliz, J., 2013. The role of consumption patterns, demand and technological factors on the recent evolution of CO_2 emission in a group of advanced economies. Ecol. Econ. 96, 1–13.
Dong, F., Yu, B., Hadachin, T., Dai, Y., Wang, Y., Zhang, S., Long, R., 2018. Drivers of carbon emission intensity change in China. Resour. Conserv. Recycl. 129, 187–201.
Fan, Y., Xia, Y., 2012. Exploring energy consumption and demand in China. Energy 40, 23–30.
Ghosh, A., 1958. Input-output approach in an allocation system. Economica 25 (97), 58–64.
González, P.F., 2015. Exploring energy efficiency in several European countries. An attribution analysis of the Divisia structural change index. Appl. Energy 137, 364–374.
Hoekstra, R., van den Bergh, J.C.J.M., 2003. Comparing structural decomposition analysis and index. Energy Econ. 25 (1), 39–64.
Kim, Y., Yoo, J., Oh, W., 2015. Driving forces of rapid CO_2 emissions growth: a case of Korea. Energy Pol. 82, 144–155.
Leontief, W., 1970. Environmental repercussions and the economic structure: an input-output approach. Rev. Econ. Stat. 52 (3), 262–271.
Liobikienė, G., Butkus, M., Bernatonienė, J., 2016. Drivers of greenhouse gas emissions in the Baltic states: decomposition analysis related to the implementation of Europe 2020 strategy. Renew. Sustain. Energy Rev. 54, 309–317.
Li, H., Wei, Y., 2015. Is it possible for China to reduce its total CO_2 emissions? Energy 83, 438–446.
Liang, S., Wang, H., Qu, S., Feng, T., Guan, D., Fang, H., Xu, M., 2016. Socioeconomic drivers of greenhouse gas emissions in the United States. Environ. Sci. Technol. 50 (14), 7535–7545.
Lin, B., Xie, X., 2016. CO_2 emissions of China's food industry: an input-output approach. J. Clean. Prod. 112, 1410–1421.
Liu, H., Xi, Y., Guo, J., Li, X., 2010. Energy embodied in the international trade of China: an energy input-output analysis. Energy Pol. 38 (8), 3957–3964.
Lim, H., Yoo, S., Kwak, S., 2009. Industrial CO_2 emissions from energy use in Korea: a structural decomposition analysis. Energy Pol. 37, 686–698.
Li, A., Zhang, A., Zhou, Y., Yao, X., 2017. Decomposition analysis of factors affecting carbon dioxide emissions across provinces in China. J. Clean. Prod. 141, 1428–1444.
Liu, Y., Meng, B., Hubacek, K., Xue, J., Feng, K., Gao, Y., 2016. 'Made in China': a reevaluation of embodied CO2 emissions in Chinese exports using firm heterogeneity information. Appl. Energy 184, 1106–1113.
NBSC, 2006-2015. China Input-Output Tables 2002-2012. National Bureau of Statistics of China.
NBSC, 2014. China Statistical Yearbook 2014. National Bureau of Statistics of China.
NBSC, 2013. China Price Statistical Yearbook 2013. National Bureau of Statistics of China.
NBSC, 2006-2013. China Energy Statistical Yearbook 2006-2013. National Bureau of Statistics of China.
NDRC, 2015. Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions. National Development and Reform Commission, Beijing.
Su, B., Huang, H.C., Ang, B.W., Zhou, P., 2010. Input-output analysis of CO_2 emissions embodied in trade: the effects of sector aggregation. Energy Econ. 32 (1), 166–175.
Su, B., Ang, B.W., 2011. Multi-region input-output analysis of CO_2 emissions embodied in trade: the feedback effects. Ecol. Econ. 71, 42–53.
Su, B., Ang, B.W., 2012a. Structural decomposition analysis applied to energy and emissions: some methodological development. Energy Econ. 34, 177–188.
Su, B., Ang, B.W., 2012b. Structural decomposition analysis applied to energy and emissions: aggregation issues. Econ. Syst. Res. 24 (3), 299–317.
Su, B., Ang, B.W., 2013. Input-output analysis of CO_2 emissions embodied in trade: competitive versus non-competitive imports. Energy Pol. 56, 83–87.
Su, B., Ang, B.W., Low, M., 2013. Input-output analysis of CO_2 emissions embodied in trade and the driving forces: processing and normal exports. Ecol. Econ. 88, 119–125.
Su, B., Ang, B.W., 2014a. Attribution of changes in the generalized Fisher index with application to embodied emission studies. Energy 69, 778–786.
Su, B., Ang, B.W., 2014b. Input-output analysis of CO_2 emissions embodied in trade: a multi-region model for China. Appl. Energy 114, 377–384.
Su, B., Ang, B.W., 2015. Multiplicative decomposition of aggregate carbon intensity change using input-output analysis. Appl. Energy 154, 13–20.
Su, B., Ang, B.W., 2016. Multi-region comparisons of emission performance: the structural decomposition analysis approach. Ecol. Indicat. 67, 78–87.
Su, B., Ang, B.W., 2017. Multiplicative structural decomposition analysis of aggregate embodied energy and emission intensities. Energy Econ. 65, 137–147.
Su, B., Ang, B.W., Li, Y., 2017. Input-output and structural decomposition analysis of Singapore's carbon emissions. Energy Pol. 105, 484–492.
Su, B., Thomson, E., 2016. China's carbon emissions embodied in (normal and processing) exports and their driving forces, 2006-2012. Energy Econ. 59, 414–422.
Shen, L., Wu, Y., Lou, Y., Zeng, D., Shuai, C., Song, X., 2018. What drives the carbon emission in the Chinese cities?-A case of pilot low carbon city of Beijing. J. Clean. Prod. 174, 343–354.
Wood, R., 2009. Structural decomposition analysis of Australia's greenhouse gas emissions. Energy Pol. 37, 4943–4948.
Weber, C.L., 2009. Measuring structural change and energy use: decomposition of the US economy from 1997 to 2002. Energy Pol. 37, 1561–1570.
Wu, R., Chen, C., 1990. On the application of input-output analysis to energy issues. Energy Econ. 12 (1), 71–76.
Wood, R., Lenzen, M., 2009. Structural path decomposition. Energy Econ. 31, 335–341.
Wang, H., Ang, B.W., Su, B., 2017a. A multi-region structural decomposition analysis of global CO_2 emission intensity. Ecol. Econ. 142, 163–176.
Wang, H., Ang, B.W., Su, B., 2017b. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Pol. 107, 585–599.
Wang, H., Ang, B.W., Su, B., 2017c. Multiplicative structural decomposition analysis of energy and emission intensities: some methodological issues. Energy 123, 47–63.
Wang, Q., Hang, Y., Su, B., Zhou, P., 2018. Contributions to sector-level carbon intensity change: an integrated decomposition analysis. Energy Econ. 70, 12–25.
Wei, J., Huang, K., Yang, S., Li, Y., Hu, T., Zhang, Y., 2017. Driving forces analysis of energy-related carbon dioxide (CO_2) emissions in Beijing: an input-output structural decomposition analysis. J. Clean. Prod. 163, 58–68.
Wang, Z., Liu, W., Yin, J., 2015. Driving forces of indirect carbon emissions from household consumption in China: an input-output decomposition analysis. Nat. Hazards 75, 257–272.
Wachsmann, U., Wood, R., Lenzen, M., Schaeffer, R., 2009. Structural decomposition of energy use in Brazil from 1970 to 1996. Appl. Energy 86 (4), 578–587.
Wang, Z., Yang, Y., 2016. Features and influencing factors of carbon emissions indicators in the perspective of residential consumption: evidence from Beijing, China. Ecol. Indicat. 61, 634–645.
Xia, Y., Fan, Y., Yang, C., 2015. Assessing the impact of foreign content in China's export on the carbon outsourcing hypothesis. Appl. Energy 150, 296–307.
Yan, J., Zhao, T., Kang, J., 2016. Sensitivity analysis of technology and supply change for CO_2 emission intensity of energy-intensive industries based on input-output model. Appl. Energy 171, 456–467.
Yang, L., Lahr, M.L., 2010. Sources of Chinese labor productivity growth: a structural decomposition analysis, 1987-2005. China Econ. Rev. 21, 557–570.
Zhang, Y., 2010. Supply-side structural effect on carbon emissions in China. Energy Econ. 32, 186–193.
Zhong, S., 2015. Structural Decompositions of Energy Consumption, Energy Intensity, Emissions and Emission Intensity a Sectoral Perspective: Empirical Evidence from WIOD over 1995 to 2009. Working paper).
Zhang, H., Lahr, M.L., 2014a. Can the carbonizing dragon be domesticated? Insights from a decomposition of energy consumption and intensity in China, 1987-2007. Energy Systems Research 26 (2), 119–140.
Zhang, H., Lahr, M.L., 2014b. China's energy consumption change from 1987 to 2007: a multi-regional structural decomposition analysis. Energy Pol. 67, 682–693.
Zhang, W., Wang, J., Zhang, B., Bi, J., Jiang, H., 2015. Can China comply with its 12th Five-Year Plan on industrial emissions control: a structural decomposition analysis. Environmental Science & Technology 49 (8), 4816–4824.